Skewness from High-Frequency Data Predicts the Cross-Section of Stock Returns*

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Abstract

Theoretical and empirical research documents a negative relation between the cross-section of stock returns and individual skewness. Individual skewness has been defined with coskewness, industry groups, predictive models, and even with options' skewness. However, measures of skewness computed only from stock returns, such as historical skewness, do not confirm this negative relation. In this paper, we propose a model-free measure of individual stock skewness directly obtained from high-frequency intraday prices, which we call realized skewness. We hypothesize that realized skewness predicts future stock returns. To test this hypothesis, we sort stocks every week according to realized skewness, form five portfolios and analyze subsequent weekly returns. We find a negative relation between realized skewness and stock returns in the cross section. A trading strategy that buys stocks in the lowest realized skewness quintile and sells stocks in the highest realized skewness quintile generates an average raw return of 38 basis points per week with a t-statistic of 9.15. This result is robust to different market periods, portfolio weightings, firm characteristics and is not explained by linear factor models.

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1 Introduction

Over the last four decades, a substantial amount of research has documented investors' preference for positive skewness over negative skewness (Arditti (1967), Kraus and Litzenberger (1976), Scott and Horvath (1980) and Harvey and Siddique (2000) among others).[1] Since investors like skewness, stocks with positive skewness earn lower returns than stocks with negative skewness. This negative relation between skewness and stock returns has been corroborated for different measures of skewness.

For example, Harvey and Siddique (2000) use coskewness, defined as the correlation between the stock's return and the market squared return, using five years of monthly data. Boyer, Mitton and Vorkink (2008) use ten years of monthly returns to compute an expected measure of skewness estimated from variables such as idiosyncratic volatility, momentum, turnover and past idiosyncratic skewness.[2] Zhang (2006) uses all stock returns from a given industry to compute a measure of skewness that is then assigned to each individual stock in that industry. Conrad, Dittmar and Ghysels (2008) and Xing, Zhang and Zhao (2009) extract skewness not from the stock market but from the options market. Even though all these measures of skewness confirm the negative relation with stock returns, a standard measure of skewness is yet to be found. The more natural place to extract skewness is the stock return distribution itself. However, it has been documented that measures based solely on the stock return distribution require large amounts of historical data and do not offer accurate estimates of expected skewness.[3] For instance, Xing, Zhang and Zhao (2009) use historical skewness as a control variable and find a positive (instead of negative) relation between stock returns and historical skewness, while Boyer, Mitton and Vorkink (2008) document that historical idiosyncratic skewness does not predict subsequent returns.

In this paper, we propose a new measure of skewness, realized skewness, extracted from the stock return distribution of high frequency data, and we test whether realized skewness predicts stock returns in the cross section. To estimate realized skewness, we extend the methodology proposed by Andersen, Bollerslev, Diebold and Ebens (2001) to compute realized volatility. Using five-minute returns, realized skewness is calculated as the sum of returns cubed over realized volatility to the power of three halves. The weekly measure is obtained as the average of the daily realized skewness measures over one week. Compared to previous measures of skewness, realized skewness

[1] See also Brunnermeier, Gollier and Parker (2007), Kapadia (2006), Barberis and Huang (2008), Mitton and Vorkink (2007), Boyer, Mitton and Vorkink (2008), Zhang (2006), Conrad, Dittmar and Ghysels (2008) and Xing, Zhang and Zhao (2009).

[2] Boyer, Mitton and Vorkink (2008) follow the approach the approach of Chen, Hong and Stein (2001) to predict idiosyncratic skewness.

[3] Zhang (2006) says that "past skewness, yet past skewness is a poor estimator of expected skewness due to data constraints: since small probability events are difficult to capture within a short period of time, a long history of returns is often required to obtain accurate skewness estimates, which puts strong restrictions on the sample and inevitably raises the concern of survivorship bias. This problem is especially severe when one estimates long term skewness—e.g., what is the probability that this company will be the next Google in five years?—because only a handful of stocks have multiple decades' return data." Kapadia (2006) says that "measuring skewness accurately for individual stocks is difficult. There is a sharp trade-off between using a large history of returns to measure skewness accurately and a smaller history to capture the time-variation of skewness."

is computed independently for each individual stock and only a week of intraday prices is necessary. Hence, our measure does not require large time series of returns (i.e. 5 years) nor information about other markets (i.e options market). Most important, realized skewness is directly extracted from the distribution of intraday stock returns in a non-parametric model-free way.

The main reason that supports the choice of intraday prices to measure asymmetries in the stock return distribution is that prices move in response to new public information and via information received in the trading process (Madhavan, Richardson and Roomans (1997)). Consequently, intraday prices not only reflect market participants' opinions instantaneously, but they also reflect how these participants adapt their views to new information and trading activity. When investors do not reach a consensus on the correct stock price, the value of stocks is affected and so is the stock return distribution (Xu (2007)). However, as new information becomes available, investors correct earlier over- and under-reactions, so that the new asset valuations reflect fundamental prices. It is precisely this trade-off between disagreement and posterior corrections of market participant views that potentially creates asymmetries on the distribution of short-term stock returns and symmetries on the distributions of long-term stock returns.

Using our new measure of skewness, we find a strong negative relation between realized skewness and subsequent stock returns. Every week, we sort stocks into quintiles based on the previous-week realized skewness and find that the trading strategy that buys the portfolio of stocks with high realized skewness and sells the portfolio of stocks with low realized skewness produces an average weekly return of -38 basis points with a t-statistic of -9.15. This value is comparable with the premium of -67 basis points per month reported in Boyer, Mitton and Vorkink (2008) and -36 basis points per month reported in Zhang (2006). Moreover, our result is validated by the Fama-French risk adjusted alpha of -39 basis points per week for the long-short portfolio.

The negative relation between stock returns and realized skewness is also supported by the Fama-MacBeth regression coefficients. Fama-MacBeth regressions of realized skewness are robust to previous-week return (Jegadeesh (1990), Lehmann (1990) and Gutierrez and Kelley (2008)), realized volatility, market size (Fama and French (1993)), book-to-market ratio (Fama and French (1993)), market beta, historical skewness, idiosyncratic volatility (Ang, Hodrick, Xing and Zhang (2006)), coskewness (Harvey and Siddique (2000)), maximum return (Bali, Cakici and Whitelaw (2009)), number of analyst in I/B/E/S, illiquidity (Amihud (2002)) and number of intraday transactions. Bivariate sorts between realized skewness and those firm characteristics show that the effect of realized skewness is still significant. Results are also robust to the month of January and prevail for NYSE stocks.

To verify that our measure of skewness is not contaminated by microstructure noise and to ensure that we are actually measuring skewness, we explore two additional measures of skewness using high frequency data. The first measure of skewness is an enhanced version of realized skewness that uses the subsampling methodology suggested by Zhang, Mykland and Ait-Sahalia (2005) to compute realized volatility. This subsampling methodology ensures that useful data is not thrown away and provides a more robust estimator of realized skewness. The second measure of skewness, SK2, is computed with the median, the 25th percentile and the 75th percentile of the stock return distribution as first proposed in Bowley (1920) and then used in Kim and White (2004). For both measures of skewness, we sort stocks, group them into quintile portfolios, and analyze the trading strategy that buys the portfolio with high skewness stocks and sells the portfolio with low skewness stocks. We find that the return of the long-short trading strategy is negative and statistically significant for these two measures of intraday skewness.

Finally, motivated by the evidence from Ang, Hodrick, Xing and Zhang (2006) that the mean-variance model does not hold for idiosyncratic volatility, we explore the relationship between realized skewness, volatility and subsequent stocks returns. Ang, Hodrick, Xing and Zhang (2006) find that stocks with high idiosyncratic volatility earn very low returns and that there is a negative relation between idiosyncratic volatility and stock returns. A possible explanation is given by Boyer, Mitton and Vorkink (2008), who, after controlling for expected idiosyncratic skewness, find that the relation between idiosyncratic volatility and stock returns is weaker and not significant. In our study, we use ex-ante realized skewness (as opposed to ex-post or expected) and find that the mean-variance model holds for stocks with low realized skewness but does not hold for stocks with high realized skewness. Hence, the risk profile, as described by the level of volatility (either realized or idiosyncratic), changes with the level of skewness. When volatility increases, low skewness stocks are compensated with higher returns and high skewness stocks are compensated with lower returns. Therefore, the inclusion of realized skewness adds an extra dimension to observe the trade-off between volatility and returns that, in turn, helps explain the idiosyncratic volatility puzzle.

This paper is organized as follows. Section two presents the computation of realized skewness and the statistical description of portfolios. Section three provides an analysis of the relationship between realized skewness and the cross-section of stock returns, robustness checks of the result using control variables, and an analysis of the interaction of realized skewness with several firm characteristics. Section four discusses the relationship between realized skewness and measures of volatility. Section five concludes.

2 Measures of Realized Moments and Data

2.1 Measures of Realized Volatility and Realized Skewness

Intraday data consists of return series that come from the logarithmic difference between prices recorded at a given frequency, typically five minutes.[4] Accordingly, on day t, the ith intraday return is given by

$$r_{t,i} = p_{t-1+\frac{i}{N}} - p_{t-1+\frac{i-1}{N}}, \tag{1}$$

[4] As argued in Andersen, Bollerslev, Diebold and Labys (2001), sampling at a five-minute rate keeps the accuracy of the continuous record assumption, while being long enough to prevent market microstructure frictions from affecting the measurements.

where p_τ is the natural logarithm of the price observed at time τ, and N is the number of five-minute intervals in a trading day.

In recent years, with the increasing availability of intraday data, many researchers have proposed realized measures of the stock return distribution. The most well-known example of these measures is realized volatility (Andersen and Bollerslev (1998), Andersen, Bollerslev, Diebold and Ebens (2001) and Barndorff-Nielsen and Shephard (2001)). Realized volatility is an estimate of the ex-post realized daily volatility that is obtained by summing squares of intraday high-frequency returns:

$$RV_t = \sum_{i=1}^{N} r_{t,i}^2. \tag{2}$$

An appealing characteristic of this volatility measure compared to other estimation methods is its model-free nature. Additionally, under certain assumptions about the underlying price process, this estimator offers several asymptotic properties (see Andersen, Bollerslev, Diebold and Labys (2001), Barndorff-Nielsen and Shephard (2002) for details).

As discussed in Dacorogna, Gençay, Mueller and Pictet (2001), it is possible to use intraday return data to construct other measures related to the time series of intraday returns. Given that we are interested on measuring the degree of asymmetry of the distribution of daily returns, we construct a measure of ex-post realized daily skewness based on five-minute returns standardized by the realized volatility as follows:

$$Skw_t = \sum_{i=1}^{N} \left(\frac{r_{t,i}}{\sqrt{RV_t}} \right)^3. \tag{3}$$

The interpretation of this measure is straightforward: negative values indicate that the stock's return distribution has a left tail that is more pronounced than the right tail, and positive values indicate the opposite. Given that our analysis is based on portfolios formed on a weekly basis, we calculate our measure of realized skewness for weekly periods as the mean of the one-day intraday skewness over the previous week as:

$$Rskw_t = \frac{\sum_{i=0}^{4} Skw_{t-i}}{5}. \tag{4}$$

2.2 Data

Our sample uses every listed stock on the Trade and Quote (TAQ) database from January 4, 1993 to June 30, 2008. TAQ provides historical tick by tick data for all stocks listed on the New York Stock Exchange, American Stock Exchange, Nasdaq National Market System and SmallCap issues.

We record prices every five minutes starting at 9:30 EST and construct five-minute log-returns for the period 9:30 EST to 16:00 EST for a total of 78 daily returns. When no price is available at exactly five minutes, we take the last recorded price in the five minute period. If no price is recorded in a period, we take the last available price so that the five-minute return in that period is zero. The end-of-day price is the first price after 16:00 EST if any; otherwise, we take the last price available for that day.

To ensure sufficient liquidity, a stock requires at least 80 daily transactions to have a daily measure of realized skewness.[5] The average number of intraday transactions per day for a stock is over one-thousand, which is well above the minimum number required. The weekly realized skewness estimator is the average of the available daily estimators (Wednesday to Tuesday). Only one valid day of realized skewness is required to have a weekly estimator and the maximum number of daily estimators is five. In addition, stocks with prices below $5 are excluded from the analysis.

Our study uses data from three additional databases. From the first database, Center for Research and Security Prices (CRSP) database, we use daily returns of each firm to calculate weekly returns (Wednesday to Tuesday), individual historical skewness, market beta, previous week return, idiosyncratic volatility, maximum return over the previous month and illiquidity; we use monthly returns to compute coskewness; we use daily volume to compute illiquidity; and we use outstanding shares and stock price to get the market capitalization. The second database is COMPUSTAT, which is used to extract the Standard and Poor's issuer credit ratings and book values to calculate book-to-market ratios of individual firms. From the third database, Thomson Returns Institutional Brokers Estimate System (I/B/E/S), we obtain the number of analysts that follow each individual firm. Definition of these variables is detailed in Appendix A.

2.3 Characteristics of Realized-Skewness-Sorted Portfolios

We construct the measure of realized skewness as outlined in equation (4) for every Tuesday in our dataset. We then sort stocks into quintiles based on their realized skewness and, within each quintile, we compute equal-weighted average characteristic values for each week. Table 1 reports the time-series average for different firm characteristic from January 1993 to June 2008. Column Q1 represents the portfolio of stocks with the smallest average realized skewness, and column Q5 is the portfolio of stocks with the highest realized skewness. Of particular interest are firms in these quintiles since they exhibit the largest degree of asymmetry in absolute value. Characteristics reported in this table include firm size, book-to-market ratio, realized volatility over the previous week, historical skewness using daily returns from the previous month, market beta coming from the market model regression, previous week return, illiquidity as in Amihud (2002), coskewness as in Harvey and Siddique (2000), idiosyncratic volatility as in Ang, Hodrick, Xing and Zhang (2006), number of analysts, credit rating, price, and number of intraday transactions.

[5] Our results still hold when the minimum number of transactions is increased to 100, 250 and 500.

[Table 1 goes here]

As Table 1 indicates, realized skewness equals to -0.087 for the first quintile and it progressively increases to a positive value of 0.086 for the fifth quintile. Firms with a high degree of asymmetry, either positive or negative, are small, highly illiquid, followed by fewer analysts and with lower number of intraday transactions. The fact that size is not negatively related to skewness contradicts previous findings by Harvey and Siddique (2000) and Chen, Hong and Stein (2001). While we find that, on average, large stocks have a realized skewness close to zero, these authors find that larger stocks tend to be more negatively skewed.

Other variables reported in Table 1 that do not vary much across realized skewness quintiles are realized volatility, beta, maximum return and price. Realized volatility takes a maximum value of 0.0024 and a minimum value of 0.0021. Market beta is above 1 for all quintile portfolios with a minimum value of 1.06 and a maximum value of 1.10. The maximum return over the previous month is very similar across quintiles ranging from 6.5% to 7.1%. Finally, no big differences are observed on the average stock price that is around $32 for all skewness quintiles.

Table 1 also reveals that realized skewness is linearly related to previous week returns. Specifically, previous week returns monotonically increase from -3.3% per week for the first quintile to 5.1% per week for the fifth quintile. This positive relation between realized skewness and contemporaneous returns is supported theoretically and empirically by Xu (2007). This fact combined with the extensive evidence that previous week returns predict subsequent returns require us to ensure that realized skewness is not a proxy of weekly returns. Previous week returns are carefully studied in the robustness check section to ensure that effect of realized skewness is different than that of previous week returns. Another variable that is positively related with realized skewness is historical skewness. Historical skewness is positive for all quintiles with a value of 0.15 for the first quintile and slightly increases to 0.19 for the fifth quintile.[6]

[Figure 1 goes here]

To further understand the realized skewness measure, we present three figures that describe different aspects of realized skewness such as the probability distribution, the historical variation of selected percentiles as well as historical values for some industries. Figure 1 displays the histogram of the cross-sectional average of $Rskw_t$ for week t over the period January 1993 to June 2008 along with the normal density function. We observe that the distribution of realized skewness is very close to the normal distribution. In unreported results, realized skewness has a mean of -0.0008, a standard deviation of 0.0124, a low negative skewness of -0.2 and a kurtosis of 3.4. Hence, the distribution of realized skewness is symmetric and does not have fat tails. Therefore, we contribute to the mixed evidence on the sign of skewness for individual stocks by stating that skewness can take positive as well as negative values with almost equal probability.

[6] Historical skewness is also included in the robustness check section.

[Figure 2 goes here]

Figure 2 plots the three-month moving average of the 10th, 25th, 50th, 75th, and 90th percentiles of $Rskw_t$ for the period January 1993 to June 2008. The cross-sectional distribution of realized skewness is symmetric throughout the sample period, as it can be observed in Figure 2. Additionally, realized skewness for all reported percentiles exhibits time variation, which is more pronounced for percentiles in the tail of the distribution. We also observe that the dispersion of realized skewness steadily increases after 1997, and it almost doubles from 1993 to 2008.

[Figure 3 goes here]

Finally, in Figure 3, we plot the three-month moving average of realized skewness for four selected industries from January 1993 to June 2008. Industry classification is similar to that of Fama and French (1997). Clearly, different industries have different values of realized skewness, with the Textile and Real State industries having more time variation than the Telecommunication and Utility industries. Moreover, realized skewness does not remain positive or negative for long periods of time. It actually revolves around zero and no specific sign can be attributed to the skewness of any industry.

3 Realized Skewness and the Cross-Section of Stock Returns

In this section we conduct three tests to assess the empirical relationship between realized skewness and the cross section of stock returns. First, we analyze whether weekly returns vary across different levels of previous week realized skewness. Second, we use the methodology of Fama and MacBeth (1973) to conduct cross-sectional regressions and determine the significance of realized skewness after controlling for several firm-related factors. Third, we perform different robustness checks to confirm the predictability of realized skewness. In particular, we test alternative measures of intraday skewness, different subsamples, and different portfolio formation definitions.

3.1 Sorting Stock on Realized Skewness

As previously explained, every Tuesday stocks are ranked into quintiles according to their previous-week realized skewness. Then, using returns over the following week, equal- and value-weighted portfolios are constructed. Table 2 reports the time-series average of weekly returns for quintile portfolios.

[Table 2 goes here]

The first row of Panel A and B shows a monotonically decreasing pattern between realized skewness and average returns. The return for the portfolio of stocks with the lowest level of skewness is 50 basis points for equal-weighted and 36 basis points for value-weighted portfolios, while the returns for stocks with the highest level of realized skewness is 12 basis points for equal-weighted and 9 for value-weighted portfolios. The return difference between Q5 and Q1 is −38 basis points for the equal-weighted and −27 for the value-weighted on a weekly basis. Both differences are statistically significant at a 1% level. Also, the main driver of these differences can be attributed to the performance of the portfolio with the lowest realized skewness. This result is consistent with recent theories stating that stocks with lower skewness command a risk premium (Kraus and Litzenberger (1976), Harvey and Siddique (2000), and Mitton and Vorkink (2007)).

In Table 2, we also assess the empirical relationship between realized skewness and stock returns by adjusting for standard measures of risk. The second row of Panel A and B in Table 2 presents, for each quintile, alphas relative to the Fama-French three factor model (excess market-return, size and book-to-market factors).[7] Note that alphas are large and statistically significant for equal- and value-weighted portfolios across quintiles. In addition, the difference between the alphas of the fifth and first quintiles is −39 and −27 basis points for equal- and value-weighted portfolios, respectively. Also, the magnitude of the alphas is very similar to that of raw returns, which shows that standard measures of risk do not offer additional adjustments to the amount of return provided from realized skewness.

The magnitude and sign of the relationship between skewness and stock returns in the cross-section is consistent with other studies that use different measures of skewness. Boyer, Mitton and Vorkink (2008) use a model that incorporates firm characteristics in order to measure the expected skewness over a given horizon. They report that the strategy that buys stocks with the highest one-month expected skewness and sells stocks with the smallest one-month expected skewness generates an average return of −67 basis points per month. Zhang (2006) measures expected skewness for a stock by allocating it into a peer group (e.g. industries) and using recent returns from this group to compute its skewness measure. The author reports that the long-short strategy produces risk-adjusted returns of −36 basis points per month.

In conclusion, Table 2 shows that realized skewness predicts the cross section of stock returns. Also, it is an important component of the cross-sectional variation in subsequent one-week returns and its magnitude and size are not captured by standard measures of risk.

3.2 Fama-Macbeth

To further assess the economic relationship between average returns and realized skewness, we carry out different cross-sectional regressions using the method proposed in Fama and MacBeth (1973). For each week t, we compute realized skewness over the previous week and then compute the following cross-sectional regression:

$$r_{i,t+1} = \gamma_{0,t} + \gamma_{1,t} Rskw_{i,t} + \phi_t' Z_{i,t} + \varepsilon_{i,t},$$

[7] We also used the Carhart (1997) four-factor model and confirm our results.

where $r_{i,t+1}$is the weekly return of the ith stock for the week $t+1$, $Rskw_{i,t}$ is the realized measure of the ith stock for week t, and $Z_{i,t}$ represent a vector of characteristics and controls for the ith firm observed at the end of week t.

[Table 3 goes here]

Table 3 reports the time-series average of the γ and ϕ coefficients for four cross-sectional regressions. The first column presents the results of the regression between the stock's weekly returns and the previous-week realized skewness. The coefficient associated with realized skewness is -0.0187 with a Newey-West t-statistic of -7.92. This result confirms the negative relation between realized skewness and stock returns.

Given the strong evidence of the return reversal effect in the short run (Jegadeesh (1990) and, more recently, Gutierrez and Kelley (2008) show it for weekly returns), we isolate the effects of previous-week returns when assessing the predictive power of realized skewness. Motivated by this finding, the second column of Table 3 includes previous-week return as a control variable. Even though the coefficient of realized skewness decreases to -0.0043, it remains significant and with negative sign. Meanwhile, the coefficient of the previous week return is negative and significant at any standard level, as expected.

Column 3 adds two control variables related to size and book-to-market. The coefficient of realized skewness is still negative and significant. Also, the negative sign of the coefficient related to size and the positive sign of the coefficient related to book-to-market confirm the standard results found in the literature. Column 4 adds a new set of control variables, which ensure that realized skewness is not a manifestation of previously documented relationships between firm characteristics and stock returns. We still find a negative and significant coefficient for realized skewness. The first set of control variables is related with illiquidity and visibility of individual stocks. This set includes number of intraday transactions, the measure of illiquidity proposed in Amihud (2002), and the number of analyst following a stock (see Arbel and Strebel (1982)). The second set of variables controls for the previously documented negative relationships between stock returns and firm characteristics such as idiosyncratic volatility (Ang, Hodrick, Xing and Zhang (2006)) as well as for the maximum daily return over the previous month (Bali, Cakici and Whitelaw (2009)). Given that realized skewness is a measure of the stock's total skewness, we also control for the stock's coskewness, as measured by the variability of the stock's return with respect to changes in the level of volatility (Harvey and Siddique (2000)). Finally, we control for the previous week volatility as measured by the mean of the daily realized volatility.

Regression results in the last two columns of Table 3 show that the economic significance of realized skewness for the cross-section of weekly returns remains robust to the inclusion of different control variables. Variables such as realized volatility, idiosyncratic volatility, and coskewness do not play a significant role on the cross-section of returns at a weekly level, while variables such as previous-week return, maximum daily return, and size do without taking away the significance of realized skewness.

3.3 Robustness

We now determine if the negative relation between realized skewness and next week returns is still present in different subsamples, robust to changes in the thresholds of portfolio formation and significant for alternative measures of intraday skewness.

3.3.1 Subsamples

In Table 3, we report value- and equally-weighted returns of portfolios sorted on realized skewness across different subsamples. Keim (1983) documents calendar-related anomalies for the month of January, in which firms experience higher price increments compared to the rest of year. The first and second rows of panel A and B in Table 5 present, respectively, the average weekly returns for the month of January and for the rest of the year for both, equal- and value-weighted portfolios. As expected, returns for the month of January are consistently higher than returns for the rest of the year. Most important, the difference between the returns of portfolios with high-skewness stocks and portfolios with low-skewness stocks is still negative and significant. This is true for equal-weighted as well as value-weighted portfolios.

We previously documented that stocks with high and low levels of skewness tend to be small. Hence, we examine that the effect of skewness is not driven by small NASDAQ stocks. By only including stocks from the New York Stock Exchange (NYSE), we confirm, as displayed in row 3 of Table 5, that the effect of realized skewness is still present among NYSE stocks. Hence, small NASDAQ stocks are not driving our results.

3.3.2 Different Portfolio Formation

In unreported results, we evaluate equal- and value-weighted average returns when stocks are sorted by realized skewness into deciles. Similar to when we sorted into quintile portfolios, we find that the higher the decile, the smaller the average weekly return and vice-versa. The difference between the returns of portfolios of stocks with the lowest and highest realized skewness increases to -43 basis points for equal-weighted portfolios and slightly decreases to -24 for the value-weighted portfolios. For both cases, the differences remain statistically significant. The Fama-French 3 factor alphas remain negative and significant with similar values to those previously reported.

3.3.3 Alternative measures of skewness

We investigate the robustness of realized skewness by computing two more measures of skewness. The first estimator uses the subsampling methodology suggested by Zhang, Mykland and Ait-Sahalia (2005), which provides robust measures to microstructure noises. This method consists of constructing subsamples that are spaced every minute. This means that instead of working with one realized measure based on a five-minute return grid, we end up working with five estimators of realized skewness using subsamples of 5-minute returns for the period 9:30 EST to 16:00 EST. Subsamples start every minute (at 9:00, 9:01, 9:02, 9:03 and 9:04), but returns remain every 5-minutes. At the end, the realized skewness estimator is computed as the average of the five estimators obtained from the subsamples.

The second alternative to intraday skewness depends solely on quartiles from the intraday return distribution. As proposed in Bowley (1920), a measure of skewness that is based on quartiles is defined as

$$SK2_t = (Q_3 + Q_1 - 2Q_2)/(Q_3 - Q_2),$$

where Q_i is the i^{th} quartile of the five-minute return distribution F, that is $Q_1 = F^{-1}(0.25)$, $Q_2 = F^{-1}(0.5)$, and $Q_3 = F^{-1}(0.75)$.

In unreported results, we find that the relationship between skewness and next-week returns is negative and statistically significant for both measures of intraday skewness.

3.4 Realized Skewness and other Firm Characteristics

This section analyzes the interaction between realized skewness and other firm characteristics such as previous-week return, size, BE/ME, realized variance, historical skewness, illiquidity, number of intraday transactions, maximum return over the previous month, number of I/B/E/S analysts, idiosyncratic volatility and coskewness.

We first sort stocks into quintiles by a firm characteristic and then, within each quintile, we sort stocks again by realized skewness into quintiles. Finally, we compute the difference of return between the highest and lowest realized skewness quintiles. This difference represents a realized skewness premium adjusted by the variable of interest.

[Table 5 goes here]

Table 5 presents the time-series average of the realized-skewness premiums from January 1993 to June 2008. We observe that realized skewness premiums for all firm characteristics are negative and statistically significant. This means that realized skewness is robust to all firm characteristics and is not a proxy for any of them. We also find that the premium is more negative for small companies with low BE/ME, low previous week returns, high realized variance, high idiosyncratic volatility, high illiquidity, high maximum return over the previous month, low number of analysts that follow the stock and high market beta. In addition, we find that the premium does not vary across different levels of historical skewness, coskewness or number of intraday transactions.

In the previous section, Fama-MacBeth regressions showed that previous-week returns have the highest explanatory power of next-week returns. The third row in Table 5 not only shows that realized skewness is negatively related with next week returns for any level of previous week return, but also that the effect is stronger for past losers (stocks with the smallest previous week return).

Also note that the negative effect of skewness is stronger among firms of small size and decreases for firms of larger sizes. This is consistent with Chan, Chen and Hsieh (1985) who show that there are risk differences between small and large firms. This phenomenon also explains why the effect of realized skewness is weaker for value-weighted portfolios when compared to equal-weighted portfolios.

Table 5 also reports that measures based on second moments have a significant role on the effect of realized skewness on next-week average returns. For example, the beta of the stock has a linear relation with the magnitude of the realized skewness effect. As the market beta increases, the long-short skewness premium becomes more negative. This pattern is also observed for idiosyncratic volatility or realized variance. In the next section, we investigate in more detail the combined effects of second and third moments on the preference for risk.

Hou and Moskowitz (2005) find that small, highly illiquid, and low visible stocks experience a high delay with which its price responds to information. As information diffusion decreases due to the delay in response of prices, investors disagreement on how to interpret new signals and on the information precision of observed prices increase. According to Xu (2007), the more investors disagree on the information, the more the skewness of the stock will be (either positive or negative). This means that firms experiencing high delay will be more prone to the effects of realized skewness, which is confirmed by the patterns observed after controlling for size, illiquidity and the number of analysts.

4 Interaction between Realized Skewness and Volatility

4.1 Realized Skewness and Realized Volatility

To further understand the role played by realized skewness on subsequent returns, we examine the effect of realized skewness and realized volatility on returns. According to asset pricing theory, investors should be compensated for bearing risk. In the Markowitz mean-variance framework, risk is defined with the level of variance. Investors holding high variance stocks are expected to earn high returns to be compensated for the higher risk they are bearing. Moreover, in the context of mean-variance, risk-averse investors prefer low variance rather than high variance stocks even if expected returns are lower. An extension of the mean-variance model includes skewness as an additional measure of uncertainty. In this context, a risk averse investor prefers stocks with positive skewness rather than negative skewness. Hence, a risk averse investor should prefer stocks with low volatility and high skewness and those stocks should earn very low returns.

To find whether this statement holds empirically, we construct portfolios with different levels of realized skewness and realized volatility and then examine subsequent stock returns. First, we form five quintile portfolios with different levels of realized skewness. Within each of these portfolios, we form five portfolios that have different levels of realized volatility.[8] Table 6, Panel

[8] Reverse sorting, that is to sorting first on realized volatility and then on realized skewness does not change the

A reports the equal-weighted returns of the 25 portfolios as well as the difference between high realized volatility quintile and low realized volatility quintile. We observe that, in low skewness portfolios, more realized volatility translates into more returns. The portfolio that buys quintile 5 (stocks with high realized volatility and low realized skewness) and sells quintile 1 (stocks with low realized volatility and low realized skewness) reports a weekly return of 77 basis points with a t-statistic of 3.31. Hence, in the group of low skewness stocks, investors are compensated with higher returns when holding high volatility stocks. A similar analysis is performed for portfolios containing stocks with positive large skewness. Surprisingly, for stocks with high skewness, we find that portfolios containing stocks with low volatility have higher subsequent returns than portfolios containing stocks with high volatility. In this case, the long-short portfolio return is -28 basis points with a t-statistic of -2.22. Therefore, investors holding stocks with high positive skewness are compensated with higher returns when those stocks have low volatility rather than when they have high volatility. Moreover, given that the portfolio with the lowest return is the one with stocks that have high skewness and high volatility, we conclude that a risk averse investor is inclined to stocks with positive skewness and high volatility. Although not as strong, a similar conclusion is reached when analyzing value-weighted portfolios as Panel B of Table 6 reports.

[Table 6 goes here]

This puzzling result is supported by Brockett and Kahane (1992). These authors theoretically demonstrate that, for the same level of skewness, a risk averse investor might choose investments with higher volatility. Golec and Tamarkin (1998) find that horse race bettors accept bets with low returns and high volatility only because they enjoy the high positive skewness offered by these bets. This conclusion is consistent with risk aversion and supports our finding that investors earn lower returns when buying stocks that simultaneously have high volatility and high skewness. Therefore, risk-averse investors, like horse race bettors, seem to like positive skewness more so than any level of volatility.

4.2 Realized Skewness and Idiosyncratic Volatility

Given that preferences for volatility change depending on the level of skewness, we now investigate whether realized skewness can explain the idiosyncratic volatility puzzle uncovered by Ang, Hodrick, Xing and Zhang (2006). In that work, the authors find that stocks with high idiosyncratic volatility earn lower returns than stocks with low idiosyncratic volatility, contradicting the mean-variance models. We replicate the idiosyncratic volatility puzzle and report the results in Table 7. For value-weighted portfolios (Panel B of Table 7), we find a weekly premium of -0.24% with a t-statistic of -1.74 for the period 1993-2007. This result is comparable to that of Ang, Hodrick, Xing and Zhang (2006) who find a monthly premium of -1.06% with a t-statistic of -3.10 for the

results.

period 1963-2000. Interestingly, as reported in Panel A of Table 7, the puzzle is not observed in equal-weighted portfolios since they do not yield significant differences across quintiles.

[Table 5 goes here]

To study the simultaneous effect that realized skewness and idiosyncratic volatility have on stock returns, we perform double sorting on both variables. We showed in Table 5 that preferences for realized skewness do not change for different levels of idiosyncratic volatility. However, given our findings that there is a positive volatility premium for low skewness and a negative premium for high skewness, we suspect that preferences for skewness might explain the idiosyncratic volatility puzzle. Hence, in this section, we analyze whether market compensation for idiosyncratic volatility changes as realized skewness increases.

To empirically analyze the returns of portfolios containing stocks with different levels of volatility and realized skewness, we first sort stocks by realized skewness and form quintile portfolios. Quintile 1 has stocks with the lowest level of realized skewness and quintile 5 has stocks with the highest level of realized skewness. Then, within each quintile portfolio, we sort stocks by idiosyncratic volatility. Table 8 reports the results for equal-weighted and value-weighted portfolios. The equal-weighted portfolio results (Panel A) are very similar to those of realized volatility reported Table 7, Panel A. In particular, we observe that the high idiosyncratic volatility portfolio (quintile 5) minus the low idiosyncratic volatility portfolio (quintile 1) premium decreases as the level of skewness increases. The premium for low realized skewness is 35 basis points and decreases to -43 basis points for the high realized skewness. We also observe that the highest return of 64 basis points is for the portfolio with high idiosyncratic volatility and low skewness and the lowest return of -20 basis points is for the portfolio with high idiosyncratic volatility and high skewness. Therefore, high idiosyncratic volatility is compensated with high returns only if skewness is low. However, investors are willing to accept very negative returns and high idiosyncratic volatility in exchange for high positive skewness.

[Table 8 goes here]

As displayed in Panel B of Table 8, value-weighted portfolios display a similar pattern than equal-weighted-portfolios with two main differences. First, the high-low premium is negative for all levels of skewness, even though, the high-low idiosyncratic volatility premium decreases as the skewness increases. This is caused by the second major difference: the portfolio of stocks with low skewness and high idiosyncratic volatility does not earn the highest returns among all portfolios. Other than those two differences, we still observe that returns of stocks with high volatility and high skewness yield very negative returns. Once again, we observe that investors trade high idiosyncratic volatility and low returns for high skewness. There is a skewness attraction effect.

Therefore, the idiosyncratic volatility puzzle is explained by two connected factors: 1) the fact the mean-variance model holds for low realized skewness stocks but does not hold for high realized skewness stocks and 2) by the empirical evidence that the portfolios of stocks with high idiosyncratic skewness reports the lowest (negative) returns of all 25 portfolios.

5 Conclusions

This paper introduces a non-parametric model-free measure of skewness, realized skewness, which is priced in the cross-section of stock returns. Realized skewness is computed for each individual stock using 5-minute returns from high-frequency data. On a weekly basis, we form quintile portfolios based on realized skewness and examine subsequent stock returns. We find a negative relation between realized skewness and stock returns. Portfolios with low skewness outperform portfolios with high skewness by 38 basis points per week. The negative relation between realized skewness and stock returns is robust to the January effect and holds for NYSE stocks. Additionally, we perform Fama-MacBeth regressions and double sortings to confirm that realized skewness is not a proxy for firm characteristics such as previous week return, size, book-to-market, realized volatility, market beta, historical skewness, idiosyncratic volatility, coskewness, maximum return over the previous month, analysts coverage, illiquidity or number of intraday transactions. Fama-MacBeth regressions and double sorting corroborate that realized skewness predicts the cross-section of stock returns.

Another contribution of this paper is the discovery that, depending on the level of skewness, high volatility is not always compensated with high returns. Analyzing portfolios that are double sorted on realized skewness and volatility, we find that stocks with negative skewness are compensated as suggested by the mean-volatility model: more volatility translates into more returns. However, as skewness increases and becomes positive, the positive relation between volatility and returns turns into a negative relation. For stocks with positive skewness, higher volatility means lower returns. Even more, the lowest returns are earned by the portfolio with stocks that have high positive skewness and high volatility. Therefore, compensation for volatility depends on the level of skewness. Stocks with low skewness are compensated with high returns when volatility increases, but stocks with high skewness are compensated with high returns when volatility decreases. This compensation for volatility presents somewhat of a puzzle given that, under the mean-variance model, investors always prefer low volatility and not high volatility as implied by our result. Hence, we argue that investors accept low returns and high volatility only because they are more attracted to high positive skewness; they are skewness lovers or lotto investors.

The fact that compensation for volatility changes depending on the level of skewness explains the idiosyncratic volatility puzzle (stocks with high idiosyncratic volatility earn very low returns) found by Ang, Hodrick, Xing and Zhang (2006). In our study, we find that portfolios with high idiosyncratic volatility stocks compensate investors with the positive returns for stock with low negative skewness and with the lowest (negative) returns for stock with high positive skewness. Consequently, the low returns earned by stocks with high idiosyncratic volatility are explained by the evidence 1) that stocks with negative skewness are compensated with positive returns and 2) that the returns of high idiosyncratic volatility portfolios is negative when skewness is low and becomes positive when skewness is high.

Finally, we leave for future research the study of the asymptotic properties of the realized skewness measure used in this paper. Additionally, a more detailed study is to be done on the determinants of realized skewness, the predictability of skewness onto daily returns and its long-term predictability. Finally, we plan to investigate the properties of intraday measures of coskewness and idiosyncratic skewness to analyze whether they are priced in the cross section of stock returns.

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Appendix A. Data Definition

- Size: following Fama and French (1993), size (in billions of dollars) is computed each June as the stock price times the number of outstanding shares. The market equity value is held constant and used from until June of the following year.

- Book-to-market: following Fama and French (1993), book-to-market is computed as the ratio of book common equity over market capitalization (size). Book common equity is defined with the COMPUSTAT book value of stockholders' equity, plus balance-sheet deferred taxes and investment tax credit minus the book value of preferred stock. The ratio is then computed as the book common equity at the end of the fiscal year over the size at the end of December of the same year.

- Historical skewness: historical skewness for each stock is defined:

$$Hskew_{i,t} = \frac{1}{N} \sum_{t=1}^{N} \left(\frac{r_{i,t} - \mu_i}{\sigma_i} \right) \tag{5}$$

  where N is the number of trading days, $r_{i,t}$ is the daily log-return of stock i on day t, μ_i is the mean over the last month for stock i and σ_i is the standard deviation of stock i for that month. In this study, we use 20 trading days to estimate historical skewness.

- Beta: beta is computed at the end of each month using daily returns over the last 12 months. We assume a single factor and estimate the following regression:

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \tag{6}$$

  where $r_{i,t}$ is the daily log-return of stock i on day t, $r_{m,t}$ is the daily return of the value-weighted index on day t and $\varepsilon_{i,t}$ is the residual of the regression for stock i on day t.

- Coskewness: following Harvey and Siddique (2000), coskewness is defined as

$$Cskew_{i,t} = \frac{E\left[\varepsilon_{i,t}\varepsilon_{m,t}^2\right]}{\sqrt{E\left[\varepsilon_{i,t}^2\right]} E\left[\varepsilon_{m,t}^2\right]} \tag{7}$$

  where $\varepsilon_{i,t}$ is obtained from

$$\varepsilon_{i,t} = r_{i,t} - \alpha_i - \beta_i r_{m,t} \tag{8}$$

  where $r_{i,t}$ is the monthly return of stock i on month t, $r_{m,t}$ is the market monthly return on month t. This regression is estimated at the end of each month using monthly returns in the last 24 months.[9]

[9] Following Harvey and Siddique (2000), we used the previous 60 months to estimate coskewness. However, our sample of firms was considerably reduced. Estimating coskewness with only 24 months, also suggested in that paper, proved to be better alternative to preserve our sample of firms.

- Previous week return: is the return over the previous week from Wednesday to Tuesday.
- Idiosyncractic volatility: following Ang, Hodrick, Xing and Zhang (2006), idiosyncratic volatility is defined as

$$idvol_{i,t} = \sqrt{var(\varepsilon_{i,t})} \tag{9}$$

where $\varepsilon_{i,t}$ is the error term of the three-factor Fama and French (1993) regression defined as

$$r_{i,t} = \alpha_i + \beta_{m,i} r_{m,t} + \beta_{SMB,i} r_{SMB,t} + \beta_{HML,i} r_{HML,t} + \varepsilon_{i,t} \tag{10}$$

where $r_{m,t}$, $r_{SMB,t}$, $r_{HML,t}$ are the Fama-French three factor model's market, size and value factors on day t and $r_{i,t}$ is the daily log-return of stock i on day t. The regression is estimated with daily returns over the previous 20 trading days.
- Maximum return: is defined as the maximum daily return over the previous month:

$$Maximum\ return_{i,t} = \max(r_{i,t}) \tag{11}$$

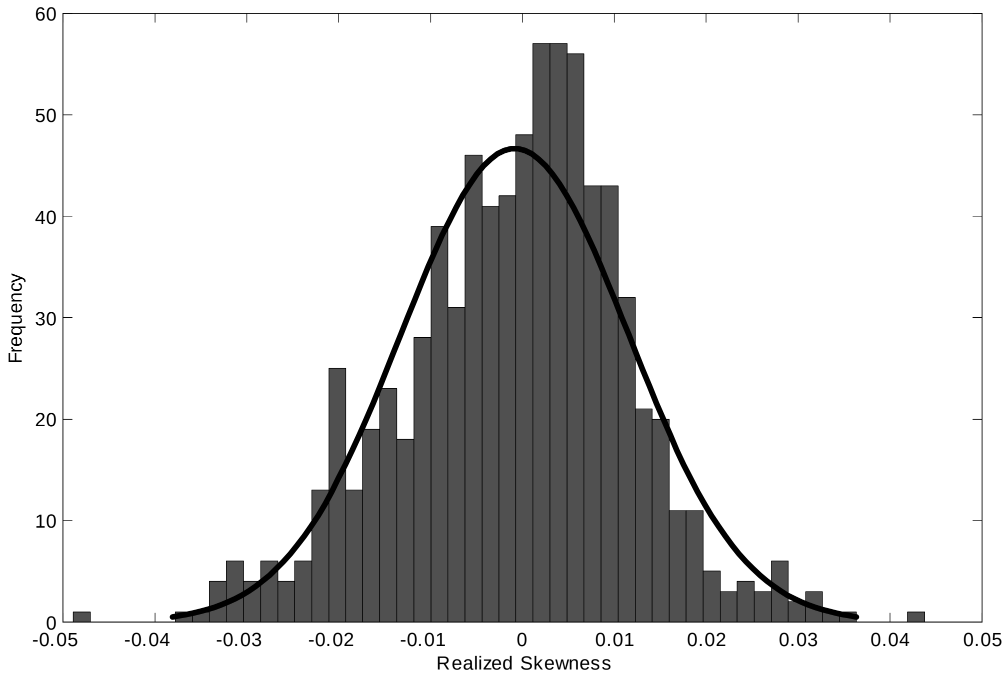
where $r_{i,t}$ is the daily log-return of stock i on day t.
- Illiquidity: following Amihud (2002), stock illiquidity is measured for any given day t as the ratio of the absolute value of the return over the dollar value of the trading volume:

$$illiquidity_{i,t} = \frac{|r_{i,t}|}{|volume_{i,t} * price_{i,t}|} \tag{12}$$

where $r_{i,t}$ is the daily log-return of stock i on day t, $volume_{i,t}$ is the daily volume of stock i on day t and $price_{i,t}$ is the price of stock i on day t.
- Credit rating is retrieved from COMPUSTAT and is then assigned a numerical value as follows: AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19, CC=20, C=21 and D=22.

Figure 1

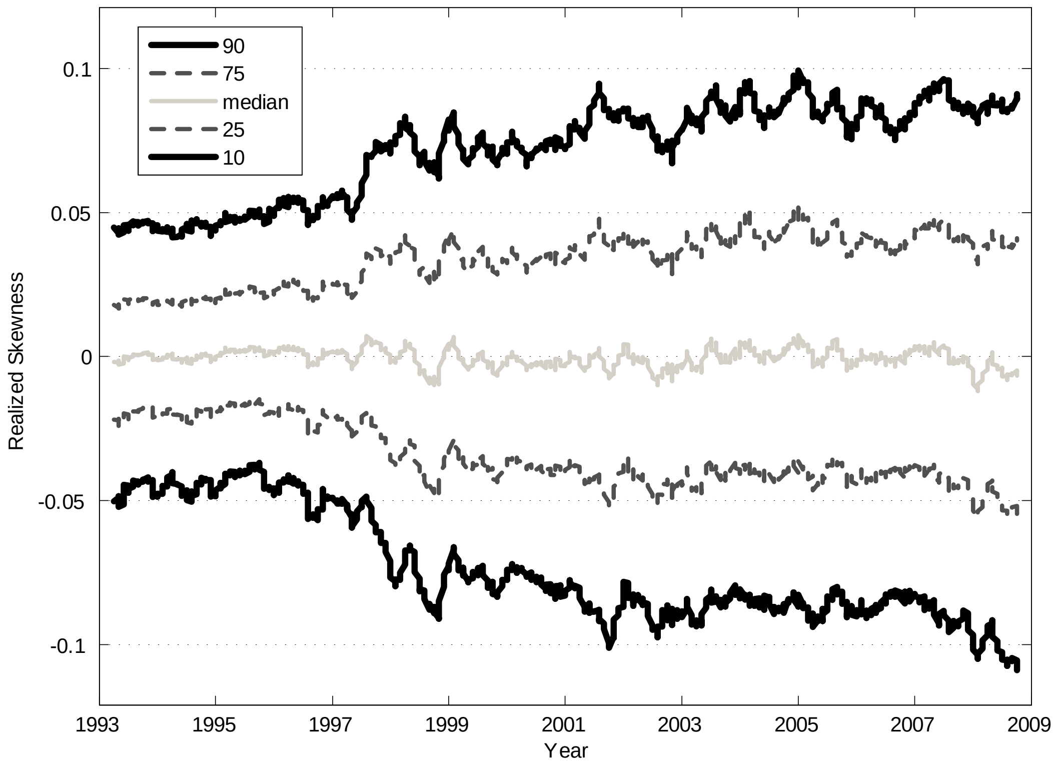
Histogram of Realized Skewness



This figure displays the histogram of the cross-sectional average of weekly realized skewness over the period January 1993 to June 2008 along with the normal density function.

Figure 2

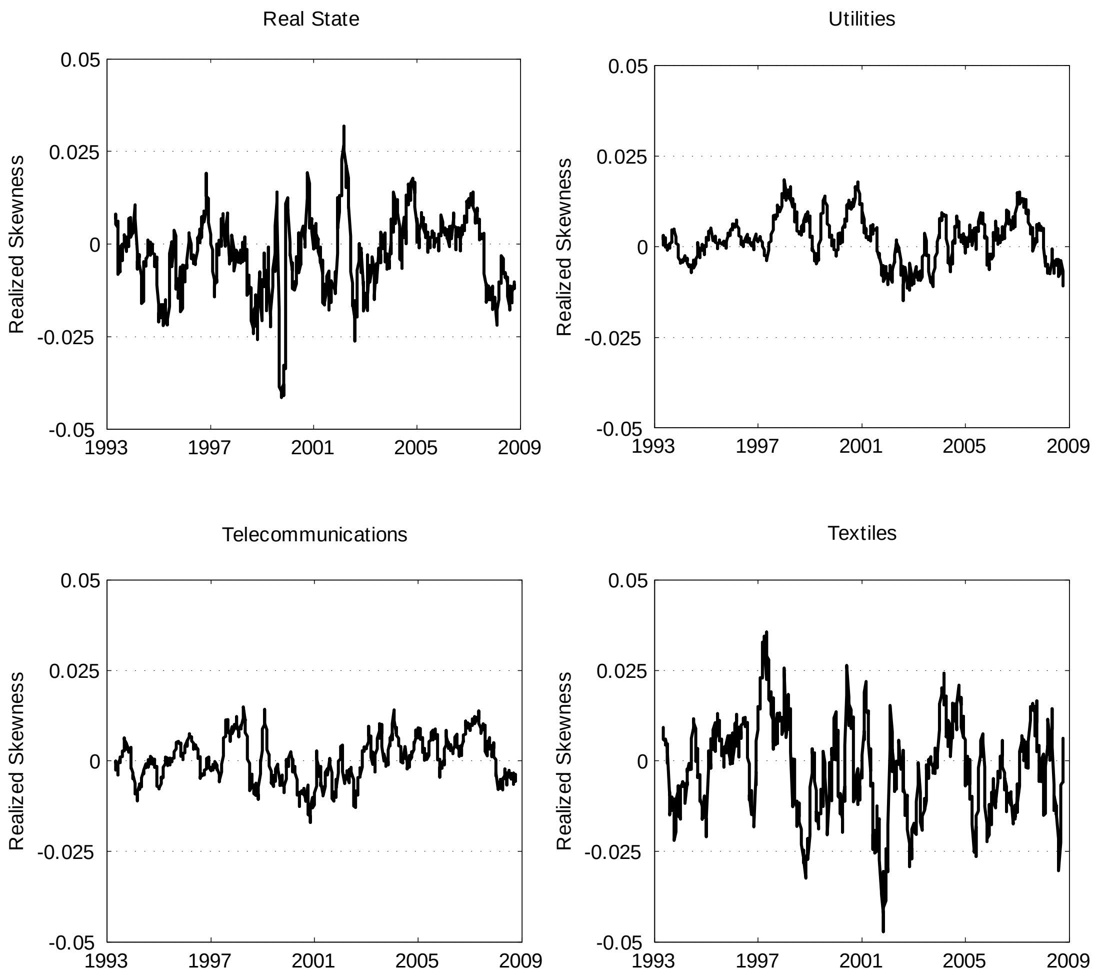
Realized Skewness Three-Month Moving Average



This figure displays the 10th, 25th, 50th, 75th and 90th percentiles of the three-month moving average of realized skewness for the cross-section of companies listed in TAQ from January 1993 to June 2008.

Figure 3

Realized Skewness of Selected Industry Groups



This figure displays the three-month moving average of realized skewness for selected industries from January 1993 to June 2008. Following Ken's French 48 industries designations, industries included in this figure are real state, utilities, telecommunications and textiles.

Table 1
Characteristics of Portfolios Sorted by Realized Skewness

Quintiles	Q1	Q2	Q3	Q4	Q5
Realized Skewness	-0.087	-0.027	0.000	0.027	0.086
Size	3.69	5.48	6.22	5.89	4.20
BE/ME	0.473	0.482	0.487	0.497	0.489
Realized volatility	0.0023	0.0024	0.0024	0.0023	0.0021
Hskew	0.150	0.165	0.164	0.173	0.196
Beta	1.10	1.12	1.10	1.11	1.06
Previous Week Return	-0.033	-0.010	0.007	0.025	0.051
Idiosyncratic Volatility	0.025	0.024	0.023	0.024	0.024
Coskewness	-0.034	-0.029	-0.026	-0.025	-0.026
Maximum Return	0.067	0.066	0.065	0.067	0.071
Illiquidity	0.00128	0.00084	0.00077	0.00079	0.00114
Number of Analysts	7.0	8.0	8.1	8.2	7.5
Credit Rating	8.4	8.3	8.3	8.3	8.3
Price	31.2	32.7	31.5	33.3	33.5
Number of Intraday Transactions	1,161	1,564	1,680	1,614	1,260
Number of Stocks	513	514	514	514	513

Each week, stocks are ranked by their realized skewness measure and sorted into quintiles. The equal-weighted characteristics of those quintiles are computed over the same week from January 1993 to June 2008. Average characteristics of the portfolios are reported for the Realized Skewness measure, Size ($ market capitalization in $billions), BE/ME (book-to-market equity ratio), Realized volatility (weekly realized volatility computed with high-frequency data), HSkew (one month historical skewness from daily returns), Beta (market beta), Previous Week Return, Idiosyncratic Volatility (computed as in Ang, Hodrick, Xing and Zhang (2006)), Coskewness (computed as in Harvey and Siddique (2000)), Maximum Return (of the previous month), Illiquidity (daily absolute return over daily dollar trading volume times 10^5, as in Amihud (2002)), Number of Analysts (from I/B/E/S), Credit Rating (1= AAA, 8= BBB+, 17= CCC+, 22=D), Price (stock price), Number of Intraday Transactions and Number of Stocks.

Table 2

Realized Skewness and the Cross-Section of Stock Returns

	Panel A: Equal-Weighted					
	Low	2	3	4	High	High-Low
Raw Returns	50.30	33.48	25.08	20.86	12.45	-37.84
	(-4.62)	(-3.14)	(-2.50)	(-2.15)	(-1.37)	(-9.15)
Alpha	49.87	34.15	25.30	21.13	12.64	-38.89
	(-4.54)	(-3.18)	(-2.50)	(-2.16)	(-1.38)	(-9.36)

	Panel B: Value-Weighted					
	Low	2	3	4	High	High-Low
Raw Returns	36.00	22.94	20.97	14.24	9.44	-26.56
	(-3.81)	(-2.35)	(-2.37)	(-1.64)	(-1.14)	(-5.09)
Alpha	36.37	23.77	22.86	15.54	10.80	-27.24
	(-3.82)	(-2.43)	(-2.59)	(-1.78)	(-1.30)	(-5.18)

This table reports the equal-weighted and value-weighted weekly returns (in bps) of quintile portfolios are formed from realized skewness, their t-statistics (in parentheses) and the difference between portfolio 5 (highest realized skewness) and portfolio 1 (lowest realized skewness) over the period January 1993 to June 2008. Panel A reports the equal-weighted portfolios and Panel B reports the value-weighted portfolios. Raw returns (in bps) are obtained from quintile portfolios sorted solely from ranking stocks based on the realized skewness measure. Alpha is the intercept from time-series regressions of the returns of the portfolio that buys portfolio 5 and sells portfolio 1 on the Carhart (1997) four factor model. Realized skewness is the weekly average of the one-day measures of skewness calculated using intraday data.

Table 3
Fama-MacBeth Cross-Sectional Regressions

	(1)	(2)	(3)	(4)
Intercept	0.0032	0.0033	0.0161	0.0166
	(3.23)	(3.34)	(5.17)	(5.81)
Realized Skewness	-0.0197	-0.0053	-0.0041	-0.0050
	(-7.89)	(-2.54)	(-2.32)	(-3.14)
Previous Week Return		-0.0257	-0.0315	-0.0393
		(-7.91)	(-10.15)	(-13.61)
log (Size)			-0.0006	-0.0016
			(-2.46)	(-6.06)
log (BE/ME)			0.0005	0.0003
			(1.62)	(1.70)
Realized Volatility				-0.049
				(-0.39)
Beta				-0.0009
				(-1.34)
Hskew				0.0018
				(9.71)
Idiosyncratic Volatility				-0.0225
				(-0.89)
Coskewness				0.0015
				(0.99)
Maximum Month Return				-0.0140
				(-2.10)
log (Number of Analysts+1)				-0.0001
				(-0.41)
log (Illiquidity)				-0.0004
				(-3.39)
log (Number of Intraday Transactions)				0.0010
				(4.25)
R^2	0.003	0.014	0.035	0.095

Results from the Fama-MacBeth cross-sectional regressions of weekly stock returns on firm characteristics are reported for the period January 1993 to June 2008. Firm characteristics are Realized Skewness, Previous Week Return, Realized Volatility (weekly realized volatility computed with high-frequency data), Size (market capitalization in $billions), BE/ME (book-to-market equity ratio), HSkew (one month historical skewness from daily returns), Idiosyncratic Volatility (computed as in Ang, Hodrick, Xing and Zhang (2006)), Coskewness (computed as in Harvey and Siddique (2000)), Maximum Return (of previous month), Number of Analysts (from I/B/E/S), Illiquidity (daily absolute return over daily dollar trading volume times 10^5, as in Amihud (2002)), and Number of Intraday Transactions. This table reports the average of the coefficient estimates for the weekly regressions along with the Newey-West t-statistic (in parentheses).

Table 4
Realized Skewness Effects for Different Subgroups

	Panel A: Equal-Weighted					
	Low	2	3	4	High	High-Low
Raw Returns, January	93.35	56.18	59.44	54.24	37.17	-56.18
	(2.73)	(1.75)	(1.97)	(1.75)	(1.31)	(-4.14)
Raw Returns, Non-January	46.29	31.37	21.88	17.75	10.15	-36.14
	(4.04)	(2.78)	(2.06)	(1.74)	(1.06)	(-8.33)
Raw Returns, NYSE	66.84	44.04	28.67	18.81	2.47	-64.37
	(4.81)	(3.08)	(2.07)	(1.40)	(0.20)	(-12.27)

	Panel B: Value-Weighted					
	Low	2	3	4	High	High-Low
Raw Returns, January	54.78	43.70	36.84	17.97	24.01	-30.77
	(2.11)	(1.46)	(1.43)	(0.68)	(0.90)	(-1.73)
Raw Returns, Non-January	34.25	21.00	19.49	13.90	8.09	-26.16
	(3.41)	(2.04)	(2.08)	(1.51)	(0.93)	(-4.79)
Raw Returns, NYSE	44.62	31.20	26.47	13.91	13.05	-31.58
	(3.08)	(2.03)	(1.82)	(1.01)	(1.02)	(-3.51)

This table reports the weekly returns (in bps) of quintile portfolios are formed from realized skewness, their t-statistics, (in parentheses), and the difference between portfolio 5 (highest realized skewness) and portfolio 1 (lowest realized skewness). Panel A reports the equal-weighted quintile portfolio returns for the month of January, for all-months excluding January, and only for NYSE stocks. Panel B reports similar results for value-weighted portfolios. Raw returns are obtained from quintile portfolios sorted solely from ranking stocks based on the realized skewness measure. Realized skewness is the weekly average of the one-day measures of skewness calculated using intraday data.

Table 5
Double Sorting on Firm Characteristics, then on Realized Skewness

	Characteristics				
	1(low)	2	3	4	5 (high)
Across Size quintiles	-77.0	-36.9	-33.7	-9.5	-16.9
Realized Skewness 5-1	(-10.23)	(-6.17)	(-6.49)	(-1.91)	(-3.66)
Across BE/ME quintiles	-58.7	-39.7	-36.0	-29.3	-24.6
Realized Skewness 5-1	(-7.91)	(-6.97)	(-6.70)	(-5.59)	(-4.33)
Across Previous Week Return quintiles	-30.5	-9.9	-9.9	-3.3	-14.3
Realized Skewness 5-1	(-5.47)	(-2.28)	(-2.50)	(-0.68)	(-2.32)
Across Realized Volatility quintiles	-10.1	-26.6	-31.4	-46.8	-88.7
Realized Skewness 5-1	(-3.72)	(-7.54)	(-6.42)	(-8.22)	(-11.44)
Across HSkew quintiles	-31.9	-37.8	-37.4	-38.1	-43.6
Realized Skewness 5-1	(-5.88)	(-7.14)	(-7.20)	(-6.87)	(-7.22)
Across Illiquidity quintiles	-27.8	-21.5	-31.6	-43.4	-67.5
Realized Skewness 5-1	(-5.66)	(-4.32)	(-6.10)	(-7.63)	(-10.88)
Across Intraday Transactions quintiles	-37.0	-37.6	-37.8	-39.4	-37.7
Realized Skewness 5-1	(-8.02)	(-7.53)	(-6.99)	(-6.13)	(-5.01)
Across Maximum Return quintiles	-17.5	-25.9	-5.3	-39.7	-57.6
Realized Skewness 5-1	(-2.20)	(-1.56)	(-0.39)	(-2.40)	(-5.76)
Across Number of Analysts quintiles	-55.8	-50.1	-39.2	-18.6	-19.4
Realized Skewness 5-1	(-8.45)	(-8.72)	(-7.38)	(-3.67)	(-3.72)
Across Beta quintiles	-29.6	-31.9	-32.8	-44.2	-62.0
Realized Skewness 5-1	(-6.34)	(-7.55)	(-6.93)	(-8.06)	(-9.01)
Across Idiosyncratic Volatility quintiles	-6.3	-20.8	-32.3	-54.0	-82.4
Realized Skewness 5-1	(-2.45)	(-6.02)	(-6.62)	(-8.68)	(-11.04)
Across Coskewness quintiles	-37.9	-16.9	-27.7	-32.9	-24.3
Realized Skewness 5-1	(-6.75)	(-3.03)	(-5.42)	(-6.42)	(-5.09)

Each week, stocks are ranked by each firm characteristic into five quintiles. Then, within each quintile, stocks are sorted once again by the realized skewness measure into five quintiles. For each firm characteristic quintile, the equal-weighted average weekly returns are reported for the realized skewness quintile difference between portfolio five and one along with the t-statistic (in parentheses). Firm characteristics are Size ($ market capitalization in $billions), BE/ME (book-to-market equity ratio), Realized Volatility (weekly realized volatility computed with high-frequency data), Previous Week Return, HSkew (one month historical skewness from daily returns), Illiquidity (daily absolute return over daily dollar trading volume times 10^5, as in Amihud (2002)), Number of Intraday Transactions, Maximum Return (of previous month), Number of Analysts (from I/B/E/S), Beta (market beta), Idiosyncratic Volatility (computed as in Ang, Hodrick, Xing and Zhang (2006)) and Coskewness (computed as in Harvey and Siddique (2000)).

Table 6
Double Sorting on Realized Skewness and Realized Volatility

Panel A: Equal-Weighted						
	1(low)	2	3	4	5 (high)	High-Low
1 (Low Realized Skewness)	30.0	42.0	43.2	59.0	77.0	47.2
	(4.50)	(4.92)	(3.70)	(4.16)	(4.47)	(3.31)
2	23.8	30.2	33.5	37.2	43.0	18.9
	(3.73)	(3.74)	(3.09)	(2.61)	(2.37)	(1.23)
3	22.5	25.3	30.0	24.2	23.0	0.6
	(3.70)	(3.28)	(3.02)	(1.77)	(1.36)	(0.04)
4	23.4	25.3	23.1	20.8	12.0	-11.7
	(3.88)	(3.33)	(2.40)	(1.60)	(0.70)	(-0.80)
5 (High Realized Skewness)	19.9	17.6	20.2	13.0	-9.0	-28.4
	(3.32)	(2.33)	(2.20)	(1.09)	(-0.56)	(-2.22)

Panel B: Value-Weighted						
	1(low)	2	3	4	5 (high)	High-Low
1 (Low Realized Skewness)	32.7	43.1	32.7	42.0	40.8	8.1
	(4.32)	(4.47)	(2.45)	(2.47)	(2.07)	(0.46)
2	25.0	25.6	24.1	25.6	14.8	-10.2
	(3.40)	(2.70)	(1.82)	(1.50)	(0.70)	(-0.55)
3	24.9	19.1	20.8	21.5	1.1	-23.7
	(3.59)	(2.11)	(1.68)	(1.35)	(0.06)	(-1.35)
4	15.4	25.5	10.6	0.7	-6.9	-22.2
	(2.27)	(2.96)	(0.88)	(0.04)	(-0.35)	(-1.25)
5 (High Realized Skewness)	12.6	8.7	14.6	6.1	-9.6	-22.2
	(1.89)	(0.95)	(1.34)	(0.44)	(-0.53)	(-1.34)

Each week, stocks are first ranked by realized skewness into five quintiles and then, within each quintile, stocks are sorted once again into five quintiles by realized volatility. Panel A reports equal-weighted returns and Panel B reports value-weighted returns. The equal-weighted and value-weighted average weekly returns (in bps) are reported for all double sorted portfolios as well as for the difference between portfolio five (High volatility) and one (Low volatility) along with the t-statistic (in parentheses) for each level of realized skewness.

Table 7
Idiosyncratic Volatility and the Cross-Section of Stock Returns

Panel A: Equal-Weighted

	Low	2	3	4	High	High-Low
Raw Returns	23.62	29.91	32.61	32.30	21.01	-2.61
	(3.96)	(3.91)	(3.29)	(2.50)	(1.31)	(-0.19)
Alpha	23.04	29.83	32.92	32.95	21.56	-3.14
	(3.85)	(3.88)	(3.31)	(2.54)	(1.33)	(-0.23)

Panel B: Value-Weighted

	Low	2	3	4	High	High-Low
Raw Returns	24.59	22.84	15.04	18.51	0.33	-24.26
	(3.46)	(2.80)	(1.46)	(1.39)	(0.02)	(-1.74)
Alpha	25.52	23.61	16.10	19.82	2.48	-24.71
	(3.60)	(2.89)	(1.56)	(1.48)	(0.15)	(-1.76)

This table reports the equal-weighted and value-weighted weekly returns (in bps) of quintile of portfolios ranked by idiosyncratic volatility, their t-statistics (in parentheses) and the difference between portfolio 5 (highest idiosyncratic volatility) and portfolio 1 (lowest idiosyncratic volatility) over the period January 1993 to June 2008. Panel A reports the equal-weighted portfolios and Panel B reports the value-weighted portfolios. Raw returns (in bps) are obtained from quintile portfolios sorted solely from ranking stocks based on the idiosyncratic volatility measure. Alpha is the intercept from the time-series regressions of the returns of the portfolio that buys portfolio 5 and sells portfolio 1 on the Carhart (1997) four factor model. Idiosyncratic volatility is the square root of the error term in the Fama-French three factor model.

Table 8
Double Sorting on Realized Skewness and Idiosyncratic Volatility

	Panel A: Equal-Weighted					
	1(low)	2	3	4	5 (high)	High-Low
1 (Low Realized Skewness)	29.3	44.0	51.9	60.5	64.0	34.8
	(4.44)	(5.05)	(4.53)	(4.27)	(3.76)	(2.48)
2	22.8	30.2	36.0	42.4	32.0	9.0
	(3.64)	(3.74)	(3.26)	(2.97)	(1.83)	(0.61)
3	23.5	26.1	28.4	28.3	17.0	-6.8
	(3.99)	(3.37)	(2.79)	(2.14)	(0.98)	(-0.47)
4	24.5	26.4	28.6	20.3	2.0	-22.9
	(4.07)	(3.47)	(2.93)	(1.56)	(0.09)	(-1.64)
5 (High Realized Skewness)	23.0	23.3	21.0	12.4	-20.0	-42.6
	(3.79)	(3.10)	(2.31)	(1.06)	(-1.32)	(-3.40)

	Panel B: Value-Weighted					
	1(low)	2	3	4	5 (high)	High-Low
1 (Low Realized Skewness)	32.1	36.1	48.9	46.6	25.1	-6.9
	(3.98)	(3.81)	(3.89)	(2.99)	(1.35)	(-0.43)
2	23.2	26.4	26.5	28.1	2.6	-20.6
	(2.91)	(2.95)	(2.19)	(1.83)	(0.13)	(-1.22)
3	30.2	22.3	12.1	21.1	0.9	-29.4
	(3.98)	(2.54)	(1.09)	(1.46)	(0.05)	(-1.90)
4	16.8	22.8	17.5	0.1	-9.5	-26.3
	(2.25)	(2.67)	(1.56)	(0.01)	(-0.53)	(-1.67)
5 (High Realized Skewness)	17.0	9.0	-1.1	8.3	-16.4	-33.4
	(2.29)	(1.01)	(-0.11)	(0.65)	(-1.03)	(-2.44)

Each week, stocks are first ranked by realized skewness into five quintiles and then, within each quintile, stocks are sorted once again into five quintiles by idiosyncratic volatility. Panel A reports equal-weighted returns and Panel B reports value-weighted returns. The equal-weighted and value-weighted average weekly returns (in bps) are reported for all double sorted portfolios as well as for the difference between portfolio five (High volatility) and one (Low volatility) along with the t-statistic (in parentheses) for each level of realized skewness.